VECTOR-BORNE AND ZOONOTIC DISEASES
Volume 8, Number 4, 2008

DOI: 10.1089/vbz.2007.0202

Meteorologically Conditioned Time-Series Predictions of West Nile Virus Vector Mosquitoes

P.R. TRAWINSKI,[1] and D.S. MACKAY[1]

ABSTRACT

An empirical model to forecast West Nile virus mosquito vector populations is developed using time series analysis techniques. Specifically, multivariate seasonal autoregressive integrated moving average (SARIMA) models were developed for *Aedes vexans* and the combined group of *Culex pipiens* and *Culex restuans* in Erie County, New York. Weekly mosquito collections data were obtained for the four mosquito seasons from 2002 to 2005 from the Erie County Department of Health, Vector and Pest Control Program. Climate variables were tested for significance with cross-correlation analysis. Minimum temperature (T_{min}), maximum temperature (T_{max}), average temperature (T_{ave}), precipitation (P), relative humidity (R_H), and evapotranspiration (E_T) were acquired from the Northeast Regional Climate Center (NRCC) at Cornell University. Weekly averages or sums of climate variables were calculated from the daily data. Other climate indexes were calculated and were tested for significance with the mosquito population data, including cooling degree days base 60 degrees (C_{DD_60}), cooling degree days base 63 (C_{DD_63}), cooling degree days base 65 (C_{DD_65}), a ponding index (I_P), and an interactive C_{DD_65}-precipitation variable ($C_{DD\_65} \times P_{week\_4}$). *Ae. vexans* were adequately modeled with a $(2,1,1)(1,1,0)_{52}$ SARIMA model. The combined group of *Culex pipiens-restuans* were modeled with a $(0,1,1)(1,1,0)_{52}$ SARIMA model. The most significant meteorological variables for forecasting *Aedes vexans* abundance was the interactive $C_{DD\_65} \times P_{week\_4}$ variable at a lag of two weeks, $E_T \times E_T$ at a lag of five weeks, and $C_{DD\_65} \times C_{DD\_65}$ at a lag of seven weeks. The most significant predictive variables for the grouped *Culex pipiens-restuans* were $C_{DD\_63} \times C_{DD\_63}$ at a lag of zero weeks, C_{DD_63} at a lag of eight weeks, and the cumulative maximum ponding index (I_{Pcum}) at a lag of zero weeks. **Key Words: West Nile—Statistical Analysis—Aedes—Culex—Vector.**

INTRODUCTION

West Nile virus (WNv) was first discovered in the Western Hemisphere during late summer 1999 when 62 human cases, including seven fatal, were found in the New York City area (Nash et al. 2001). Since its initial detection, it has spread to birds and mosquitoes throughout the 48 states of the continental United States (USGS National Biological Information Infrastructure, May 15, 2006). WNv has been found in birds within Erie County, New York, every season since its initial appearance in 2000, and the virus has been detected in the mosquito pools since 2002, which is evidence that it is quickly establishing itself enzootically. In 2002, Erie County experienced nine human cases of WNv, including one death. Because WNv is expected to be present in low levels in the local environment for the foreseeable future, control efforts will be aided by determining when the vector species are most abundant. The objective of this study was to develop a temporal model of WNv mosquito vector populations using Erie County mosquito control data in order to forecast mosquito abundance as a proxy for disease risk. We hypothesized that incorporating meteorological data in the temporal model would improve prediction of potentially epidemic seasons for WNv. Temporal analysis has previously been used to forecast incidence of malaria, Ross

[1]Department of Geography, State University of New York at Buffalo, Buffalo, New York.

River virus, Barmah Forest virus disease, and *Campylobacter* infections (Allard 1998, Tong et al. 2002, Abeku et al. 2004, Hu et al. 2004, Tong et al. 2004, Naish et al. 2006).

A lack of vaccination or other prevention options for West Nile fever and neurological disease places great importance on mosquito control efforts to control the disease. The relationship between climate and West Nile virus epidemics has not been quantified, and consequently there is no climate-based early warning system for WNv in the United States or in other areas that are traditionally prone to epidemics of the virus (Leaf 1989, Kuhn et al. 2004). Research on mosquito vectors has been largely concentrated in tropical and subtropical climates where malaria and dengue fever are the primary disease concerns, but with global climate change and increasing international transportation of people and goods, the study of mosquito vectors in more temperate climates is receiving more attention (Longstreth 1999). Most previous studies that focus on the link between disease incidence and climate have used monthly climate and incidence data because of small weekly disease counts; however, a finer temporal resolution of data is possible when using vector count data, and this resolution will allow a more specific forecast to be made in time (Abeku et al. 2004, Hu et al. 2004).

Presumed vectors of West Nile virus in Erie County are *Aedes vexans*, *Culex pipiens*, and *Culex restuans*, the last two forming the grouped *Culex pipiens-restuans* complex (ECDOH 2005). The *Cx. pipiens-restuans* complex data will be used, because it is almost impossible to distinguish between the two similar species as adults (DeGaetano 2005, Diuk-Wasser et al. 2006). *Culex pipiens* and *Culex restuans* have similar feeding behavior and breed in similar habitats. These two species have been grouped in previous studies (DeGaetano 2005, Kilpatrick et al. 2005, White et al. 2006). *Culex pipiens-restuans* and *Aedes vexans* mosquitoes prefer different habitats. *Cx. pipiens-restuans* mosquitoes are a known primary vector of WNv that prefer water habitats with a high organic content, often associated with storm water runoff (Turell et al. 2000, Kilpatrick et al. 2005, Turell et al. 2005). *Ae. vexans* mosquitoes are known to carry WNv and are prolific human biters, allowing for transmission of the virus to humans (Hayes et al. 1985, Andreadis et al. 2004, ECDOH 2005, Turell et al. 2005). They are called "floodwater mosquitoes" because larvae are found in practically all temporary pools of water. Eggs are laid on the ground, and they hatch when flooded with fresh water (Hayes et al. 1985, Pratt and Moore 1993).

Identification of meteorological factors and landscape features associated with the distribution and abundance of vector species is a necessary step toward eliminating suitable vector habitats and thus minimizing the risk of human WNv infection (Campbell et al. 2002, CDC 2003). This is the overall goal of the research study. Here, we focus on the regional meteorological factors through temporal modeling.

MATERIALS AND METHODS

Erie County, New York, is located in the western region of New York State, bordering the northeastern shore of Lake Erie. Erie County encompasses the City of Buffalo and its suburbs, and the county has a total area of 263,186 hectares or approximately 2664 square kilometers (Soil Survey of Erie County, New York). The 2005 population estimate for the county is 930,703, of which 15.6% is over the age of 65, and 5.7% is under the age of 5 (U.S. Census Bureau, 9/5/06). The soils and surficial geology of Western New York in general are typified by glacial characteristics. At the end of the Wisconsin Glaciation, approximately 10,000 years before present, glacial Lake Tonawanda and other glacial lakes occupied the area. The surficial geology includes ice-contact glacial materials (e.g., till plains and moraines) with poorly sorted materials, laminated silt and clay deposited on the lake bottoms, and sand deposited on beach ridges and more recent floodplains. Because of extensive floodplains and slightly elevated interfluve areas, the soils range from hydric to nonhydric with a corresponding range in textures from silt and clay dominated to sand dominated.

All mosquito data were obtained from the Vector Control Program of the Erie County Health Department. The Erie County Department of Health established the Vector Control Program in 2001, primarily in response to the new threat of the arboviral West Nile virus (ECDOH 2005).

The Vector Control Program traps adult mosquitoes mostly with Miniature CDC Light Traps baited with carbon dioxide. This type of trap is designed to attract and capture biting females. Trapping is performed to a lesser extent with Gravid traps, which utilize a container of water with a high organic content as an attractant for female mosquitoes ready to lay eggs ("gravid females"). Gravid traps primarily catch *Culex species* mosquitoes; however trap counts can be negatively affected when other sources of stagnant water are nearby. Trapping is conducted by the Vector Control Program on a weekly basis at nine permanent trapping sites located throughout Erie County. The traps are set in the afternoon and are retrieved the following morning once a week throughout the mosquito season. The mosquito season lasts approximately 20 weeks from early May to early October in Western New York. Specifically, the Vector Control Program conducts trapping when the overnight temperature is greater than 50°F or 10°C. Collected mosquitoes are transported to the Vector Control Lab, where the trap nets are placed in an ultra-low freezer for 15 min at –70°C to immobilize the mosquitoes. The mosquitoes are identified on a chill table using established procedures (Carpenter and LaCasse 1955, Stojanovich 1961, Means 1979, Means 1987).

The data used in the current study consist of all CDC Miniature Light Trap data from Walden Pond Park in Lancaster, New York. This site was chosen because of its proximity to the Buffalo Niagara International Airport, where the weather data were collected. Gravid trap data were not used in the analysis, because the trap catch is affected by stagnant water located nearby. Also, the number of *Culex sp.* caught in these traps is affected by the pungency of the water (ECDOH 2005).

Daily maximum temperature, minimum temperature, average temperature, precipitation, and relative humidity were obtained for the Buffalo Niagara International Airport from the Northeast Regional Climate Center (NRCC) located at Cornell University. Actual evapotranspiration (E_T) was calculated from a modified British Meteorological Office Rainfall and Evaporation Calculation System (MORECS) to provide operational estimates of evaporation and soil moisture for grass cover at the Buffalo airport. MORECS is based on a variation of the Penman-Monteith Equation for operational use in the northeast, and the system uses solar radiation, air temperature, vapor pressure, and wind speed to estimate actual evapotranspiration. The daily estimates monitor weather closely and provide for water stored in the soil. The model was run at the NRCC for October 1, 2001, to September 30, 2005. Several predictive variables were derived from the weather data and model results. Cooling degree days base 60 (C_{DD_60}), cooling degree days base 63 (C_{DD_63}), and cooling degree days base 65 (C_{DD_65}) were calculated as follows:

$$C_{DD\_n} = 0.5 \cdot (T_{\max} + T_{\min}) - T_{\mathrm{n}} \tag{1}$$

where $T_{\max}$, $T_{\min}$, and T_{n} represent maximum, minimum, and base temperatures (°F), respectively.

Net precipitation (P_{net}) was calculated as

$$P_{net} = P_{day} - E_T \tag{2}$$

where P_{day} is daily precipitation [cm]. A number of alternative ponding indices were derived to account for soil ponding. A dynamic ponding index (I_{P}) [cm] that accounts for soil water capacity and drainage (surface runoff or deep drainage to groundwater) over time was calculated as follows:

$$I_{P_i} = I_{P_{i-1}} + P_{net_i} - R_i, \quad -18 \le I_{P_i} \le 8 \tag{3}$$

where i is the current day, i-1 is the previous day, and R_{i} is a water loss (runoff or deep drainage) term calculated as

$$R_i = \begin{cases} \alpha \cdot I_{P_{i-1}} & , I_{P_{i-1}} > 0 \\ 0 & , I_{P_{i-1}} \le 0 \end{cases} \tag{4}$$

and α is a parameter (= 0.05). The other indices were maximum ponding (I_{Pmax}), cumulative maximum ponding (I_{Pcum}), and ponding index per water year (I_{Pwy}), which were calculated as follows:

$$I_{P\max} = \begin{cases} P_{net} & , P_{net} < 0.16 \\ 0.16 & , P_{net} \ge 0.16 \end{cases}, \tag{5}$$

$$I_{Pcum} = \sum_{i=1}^{1} I_{P\max_i}, \text{ and} \tag{6}$$

$$I_{Pwy} = \sum_{i=1}^{m} P_{net_i} \tag{7}$$

where l is days since start of simulation and m is days since the beginning of the water year (October 1). To capture the interactivity between temperature and precipitation, we took the product of C_{DD_65} at a lag of zero weeks and precipitation at a lag of four weeks ($C_{DD\_65} \times P_{week\_4}$).

Daily climate normal maximum temperature, minimum temperature, average temperature, precipitation, and cooling degree days base 65 were obtained from the National Weather Service and were used to calculate daily departures from normal from these variables. The daily data were then aggregated into weekly departures from normal. Most climate variables were multiplied by themselves and were subsequently analyzed with the rest of the climate variables to assess nonlinear relationships between climate and vector abundance.

A time series is any set of N time-ordered observations of a process. Two main methodological approaches to time series analysis are harmonic analysis and regression analysis. Regression analysis, or "analysis in the time domain," includes Autoregressive Integrated Moving Average (ARIMA) models that can be traced historically over 70 years (McCleary and Hay 1980). Despite a long history as a statistical tool, ARIMA modeling did not become popularized until Box and Jenkins (1976) integrated the elements into a comprehensive theory. The basic tenet of the Box-Jenkins approach posits a random shock (a_t) as the driving force of a time series process (Y_t). The most important determinant of the output is the current input, but previous input and previous output may also influence the current output:

$$Y_t = \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2}. \quad (8)$$

where, Y_t is the output at time t, $Y_{t\text{-}n}$ is the output at time t-n, a_t is the input at time t, $a_{t\text{-}n}$ is the input at time $t\text{-}n$, Φ_n is the output parameter, and θ_n is the input parameter.

The influence of a past event or input on present events diminishes as time passes. Because the present input, a_t, will have a greater impact on the present output than any earlier input, and the parameter, θ, must be a fraction, therefore $1 > \theta_1 > \theta_2 > \ldots > \theta_q$. The same principle applies to influence past outputs, such that $1 > \Phi_1 > \Phi_2 > \ldots > \Phi_p$. These principles are called the bounds of stationarity-invertibility and must be assessed when estimating parameters of an ARIMA model (Box and Jenkins 1976, McCleary and Hay 1980, Box and Jenkins 1990).

Time series analysis consists of procedures used to build models of the processes that generate the series. The ARIMA model building strategy is an iterative process of identification, estimation, and diagnosis. For simple ARIMA model building, three types of components must be identified: the autoregressive (p), the integrated (d), and the moving average (q) (McCleary and Hay 1980, SPSS 2004). For seasonal ARIMA model building, three more types of components must be identified: the seasonal autoregressive (P), seasonal integrated (D), and seasonal moving average (Q). Autoregressive processes have "memory" and are better for modeling long-term fluctuations; each value in the series is a linear function of the preceding value but has a diminishing effect on subsequent time periods. An integrated process often reflects the cumulative effect of some process that is responsible for changes in the level of the series but is not responsible for the level itself. Moving average processes are best for modeling short-term fluctuations by predicting future values of the series based on deviations from the series mean for previous values (McCleary and Hay 1980, SPSS 2004).

Identification of $(p,d,q)(P,D,Q)_S$ models depends primarily on the autocorrelation function (ACF) and secondarily on the partial autocorrelation function (PACF). The autocorrelation function is a measure of correlation between Y_t and some Y_{t+k} time units away:

$$\text{ACF}(k) = \text{COV}(Y_t\, Y_{t+k}) / \text{VAR}(Y_t). \quad (9)$$

Although the ACF can be represented as a simple equation in terms of the covariance and variance of time series, the PACF cannot be summarized in equation form so simply but is defined as a measure of correlation between time series observations k units apart after the correlation at intermediate lags has been partialed out or controlled for (McCleary and Hay 1980). In general, certain patterns to the ACF and PACF can help identify the structure of a model. Autoregressive models have exponentially declining values of the ACF graph and have p spikes in the first p values of the PACF graph. Moving average models have exponentially declining PACF graphs and have q spikes in the first q values of the ACF graph. Differencing of the time series was performed before identifying the AR and MA components. The need for differencing was evident when ACF values declined slowly (SPSS 2004). Differencing can be described as amounting to subtracting the first observation from the second, and differencing can be performed both simply and seasonally (McCleary and Hay 1980). Seasonal, autoregressive, integrated, and moving average components were identified by looking at the ACF and PACF at the seasonal lags of the series. In practice, seasonal ARIMA models are often difficult to identify, and patterns in the ACF and PACF are open to interpretation. Akin to the autocorrelation function, the cross-correlation statistic measures the between-series correlation. Cross-correlation between two nonstationary time series is regarded as spurious, and prewhitening of the two series was necessary to find the true relationship between the dependent and independent series (McCleary and Hay 1980). The independent variables were assessed within the ARIMA model, being treated much like predictor variables in regression analysis. Parameter coefficients and associated significance values are estimated for a set of independent variables that best fits the data (SPSS 2004).

The following steps were used to identify a model. First, an analysis of stationarity determined the differencing and transformations necessary to obtain a stationary series. A time series must be stationary with respect to the mean and the variance for adequate modeling (McCleary and Hay 1980, Allard 1998). Differencing was performed on the series to make the mean stationary, and transformations were used to make the variance stationary. Second, the ACF and PACF plots were examined to estimate values of p and q. An ARIMA $(p,d,q)(P,D,Q)_S$ model must be identified on the basis of the entire autocorrelation (ACF) and partial autocorrelation (PACF) plots. Third, the ACF and PACF plots were examined at seasonal lags to determine the value of Q and P (McCleary and Hay 1980). After a possible model was identified, the parameter estimates were examined for statistical significance and checked with the bounds of stationarity–invertibility. The model identification process was repeated until these conditions were met. After the final models were obtained, the residuals were analyzed and judged by two criteria. Their autocorrelation function and partial autocorrelation function were assessed for spikes at key lags to determine if the residuals are white noise. The Box-Ljung Q-statistic was inspected for significance at lags of about a quarter of the series and at seasonal lags.

Values from two dates within the weekly trapping data were missing and were linearly interpolated, replacing the missing values. The natural log of the mosquito data plus one was used for analysis in order to normalize the count data. Daily weather data were aggregated into weekly data following the same weekly schedule as the mosquito trapping data from the Vector Control Program. Univariate/bivariate analyses were conducted for each independent variable.

Box-Jenkins prewhitening was conducted on both the predictor and target series to eliminate any autocorrelations and seasonalities common to both the predictor and target series. Univariate models were constructed for each of the predictor variables, and these models are then applied to the mosquito data to obtain the residuals. The residuals from the predictor series and the residuals of the target series were used in the cross-correlation analysis. A series of correlations between climate variables and the natural logarithm of the count of vector mosquitoes over a range of time lags were computed for cross-correlation analysis.

Both mosquito and climate data were transformed into stationary input series by both regular and seasonal differencing before being modeled. SARIMA models were developed using the weekly incidence of mosquito counts as a response variable and weekly climate variables as explanatory variables. Six main components were selected, with the model defined as:

$$y_t = Q_q(B)\ Q_Q(B^s)\ a_t\ (f_p(B^s)/ f_p(B^s))\ f_p(B)(1 - B)d(1 - B^s)^D + P, \quad (10)$$

where $Q_q(B)$ is a moving average operator, $Q_Q(B^s)$ is a seasonal moving average operator, $f_p(B)$ is an autoregressive operator, $f_p(B^s)$ is a seasonal autoregressive operator, a_t is white noise, and P represents the explanatory variables' regressive coefficients.

We selected SARIMA models by first examining the residual variance, or root mean square error, for appropriateness, and then we applied Akaike's Information Criterion (AIC) as a measure of how well the model fit the series. The root mean square (RMS) error is a measure of the predictive ability of the model, where a smaller RMS error translates to a better model in terms of forecasting. An autoregression $(2,1,0)(1,1,0)_{52}$ SARIMA model was developed for *Ae. Vexans*, whereas a moving average and seasonal autoregression $(0,1,1)(1,1,0)_{52}$ model was developed for *Cx. pipiens-restuans*. Environmental variables were selected for inclusion by first identifying significant lags in the cross correlation analysis. Also, the explanatory variables were further investigated with a regression method. However, the final variables chosen for inclusion in the model were added to the model one by one and were selected based on comparisons of the SARIMA models with and without inclusion of the extra variables (Alberdi Odriozola et al. 1998). Goodness of fit of the models was assessed using both times series methods to check for autocorrelation of residuals and classic tools to check the normality of residuals. The model was verified by dividing the data set into two time periods: Data between October 2001 and December 2004 were used to construct the SARIMA model, whereas data between January and October 2005 were used to validate the model. All analyses were performed using SPSS Trends version 13.0 and version 14.0 (SPSS Inc., Chicago, IL).

RESULTS

Summary statistics for each explanatory variable are shown in Table 1. The weekly mean maximum temperature, minimum temperature, average temperature, relative humidity, total precipitation, and evapotranspiration were 13.64°C, 4.80°C, 9.23°C, 74.41 percent, 1.99 centimeters, and 1.00 centimeters, respectively, throughout the study time period. Weekly mean total C_{DD_60}, C_{DD_63}, and C_{DD_65} were 22.03, 15.23, and 11.44, respectively. C_{DD_65} is equivalent to cooling degree days based on 18.33°C, whereas C_{DD_63} is equivalent to 17.22°C, and C_{DD_60} is equivalent to 15.56°C, respectively. The means of the I_P and $C_{DD\_65} \times P_{week\_4}$ variable were 1.20 centimeters and 19.71 centimeter degree days, respectively. There appeared to be positive relationships between climate variables and populations of vector mosquitoes as evidenced by bivariate analyses.

Mosquito data from the Erie County Department of Health, Vector Control Program, contains information on 81 trap-nights when overnight temperature conditions were above minimum levels established for trapping. The mean number of mosquitoes captured per trap-night is 52.5 for *Ae. vexans*, with a range from 0 to 521. The mean is 5.2 for *Cx. pipiens-restuans*, with a range from 0 to 72, respectively. Examination of probability-probability (p-p) plots of the original count data, and the natural log of the data plus one, showed a significant improvement in normality and, so the log transformed data was used for subsequent analyses.

Cross-correlation analysis showed significant correlation between *Ae. vexans* populations and minimum temperature, relative humidity, precipitation, evapotranspiration, all of the cooling degree day variables, and cumulative C_{DD_60} at various lags (Table 2). Ponding index, $C_{DD\_65} \times P_{week\_4}$, P_{net}, I_{Pwy}, I_{Pmax}, and precipitation departure from normal also had various correlated lags. The squared climate variables for maximum temperature, minimum temperature, average temperature, evapotranspiration, precipitation, relative humidity, C_{DD_60}, C_{DD_63}, C_{DD_65}, and net precipitation also showed correlated lags with *Ae. vexans* populations. All of the significant lags of these variables were tested for statistical significance in the ARIMA model. Maximum temperature, average temperature, cumulative maximum ponding, cumulative C_{DD_65}, maximum temperature departure, minimum temperature departure, average temperature departure and C_{DD_65} departure were not significant at any lag (Table 2 and Fig. 1).

Relative humidity, precipitation, all C_{DD} variables, ponding index, $C_{DD\_65} \times P_{week\_4}$, net precipitation, I_{Pwy}, I_{Pmax}, I_{Pcum}, cumulative C_{DD_60}, cumulative C_{DD_65}, and precipitation departure from normal had significant lags when cross-correlated with *Cx. pipiens-restuans* (Table 2). Average temperature, precipitation, relative humidity C_{DD_63}, and net precipitation squared variables had significant lags when cross-correlated with *Cx. pipien-restuans* populations. Minimum temperature, maximum temperature, average temperature, evapotranspiration, maximum temperature departure, minimum temperature departure, average temperature departure, and C_{DD_65} departure were not correlated with the mosquito populations. The squared variables of maximum temperature, minimum temperature, average temperature, evapotranspiration, C_{DD_60}, C_{DD_63}, and C_{DD_65} also were not correlated with the *Cx. pipiens-restuans* populations (Table 2 and Fig. 2).

Four SARIMA models for *Ae. vexans* and *Cx pipiens-restuans* populations are presented in Tables 3 and 4, respectively. The model without climate variables includes autoregressive 1 ($\beta = -0.4592$, $p < 0.001$) autoregressive 2 ($\beta = -0.2493$, $p = 0.001$), and seasonal autoregressive ($\beta = -0.4097$, $p < 0.001$) parameters that were significantly associated with the weekly mosquito counts. The residual variance of the univariate model was 0.768 and the AIC was 414.579 (Table 5). Three weekly climate variables contributed significantly to the model (Fig. 3). $C_{DD\_65} \times P_{week\_4}$ lag two ($\beta = 0.0032$, $p = 0.002$) was significant in the SARIMA

Table 1. Characteristics of Independent Variables

Weekly variables	*Units*	*Mean*	*Standard deviation*	*Minimum*	*Maximum*
Maximum temperature	°C	13.64	10.49	−8.49	31.98
Minimum temperature	°C	4.80	9.50	−16.27	21.11
Average temperature	°C	9.23	9.95	−12.38	26.31
Relative humidity	%	74.41	6.31	46.44	89.86
Precipitation	cm	1.99	1.83	0.00	10.21
Evapotranspiration	cm	1.00	0.78	0.03	3.30
Cooling degree days 60	Degree days	22.03	33.94	0.00	135.50
Cooling degree days 63	Degree days	15.23	26.30	0.00	112.50
Cooling degree days 65	Degree days	11.44	21.24	0.00	100.50
CDD-precipitation	cm Degree days	19.71	55.52	0.00	554.33
Precipitation-evapotranspiration	cm	0.99	2.06	−3.15	9.20
Ponding index per water year	cm	241.50	114.03	−0.61	451.94
Maximum ponding	cm	−0.03	1.04	−3.15	2.08
Cumulative maximum ponding	cm	63.68	48.67	−52.05	137.79
Ponding index	cm	1.20	4.46	−9.03	13.55
Cumulative cooling degree days 60	Degree days	483.33	503.78	0.00	1416.00
Cumulative cooling degree days 65	Degree days	248.28	276.28	0.00	844.50
Maximum temperature departure	°C	0.48	6.30	−14.00	16.71
Minimum temperature departure	°C	0.60	5.57	−15.43	14.43
Average temperature departure	°C	0.57	5.77	−13.93	15.50
Precipitation departure	cm	0.00	0.11	−0.14	0.55
Cooling degree days 65 departure	Degree days	8.57	53.09	−33.50	396.00
Maximum temperature × maximum temperature	°C^2	295.44	282.00	0.06	1022.98
Minimum temperature × minimum temperature	°C^2	112.97	116.85	0.00	445.68
Average temperature × average temperature	°C^2	183.77	188.96	0.00	692.19
Weekly variables					
Precipitation × precipitation	cm^2	7.29	14.29	0.00	104.26
Evapotranspiration × evapotranspiration	cm^2	1.62	1.92	0.00	10.90
Relative humidity × relative humidity	%	5575.76	920.84	2156.72	8074.31
Cooling degree days 60 × cooling degree days 60	degree days 2	1631.24	3331.85	0.00	18360.25
Cooling degree days 63 × cooling degree days 63	degree days 2	920.31	2184.55	0.00	12656.25
Cooling degree days 65 × cooling degree days 65	degree days 2	579.62	1514.26	0.00	10100.25
(Precipitation–evapotranspiration) × (precipitation–evapotranspiration)	cm^2	5.19	10.81	0.00	84.59

Note: All variables have $N = 209$ except CDD–Precipitation, which has $N = 205$.

TABLE 2. SIGNIFICANT LEADING INDICATOR CLIMATE VARIABLES FROM CROSS-CORRELATION ANALYSIS[a]

	Aedes vexans	*Culex pipiens-restuans*
Maximum temperature	–	–
Minimum temperature	12, 16	–
Average temperature	–	–
Relative humidity	6, 7, 8	2, 3, 10
Precipitation	1, 4, 5, 7, 10, 11, 13, 14	0, 5, 6, 9, 10, 15, 16
Evapotranspiration	2, 3	–
Evapotranspiration × evapotranspiration	2, 3, 5	–
Cooling degree days 60	1, 2, 6, 7	0, 5
Cooling degree days 63	1, 2	0, 8
Cooling degree days 65	1, 6, 7	0, 5
Ponding index	4, 5, 10, 11	9, 15
CDD-precipitation	2, 3, 4, 5, 12	4, 5
Net precipitation	1, 4, 5, 7, 10, 11, 13, 14	0, 5, 6, 9, 10, 15, 16
Ponding index per water year	3, 15	9, 11, 12, 13
Maximum ponding	1, 3, 4, 6, 7, 11	3, 5, 6
Cumulative maximum ponding	–	0, 8
Cumulative cooling degree days 60	12	15, 16
Cumulative cooling degree days 65	–	15
Maximum temperature departure	–	–
Minimum temperature departure	–	–
Average temperature departure	–	–
Precipitation departure	4, 5, 10, 11	9, 10, 15
Cooling degree days 65 departure	–	–
Maximum temperature × maximum temperature	1, 2	–
Minimum temperature × minimum temperature	1, 6, 7	–
Average temperature × average temperature	1, 2, 6, 7	5
Precipitation × precipitation	4, 5, 10, 11, 13	0, 5, 9, 10, 12
Relative humidity × relative humidity	6, 7, 8	2, 3, 10
Cooling degree days 60 × cooling degree days 60	1, 2, 6, 7	–
Cooling degree days 63 × cooling degree days 63	1, 2, 7	0
Cooling degree days 65 × cooling degree days 65	1, 2, 6, 7	–
Net precipitation × net precipitation	0, 4, 5, 10, 11, 13, 14	0, 9, 10, 12

[a]Correlations are significant at the 0.05 level.

model, improving the residual variance to 0.735 and the AIC to 402.452 (Table 5). By including $E_T \times E_T$ lag five ($\beta = -0.1369$, $p = 0.011$), the residual variance improved to 0.726, and AIC decreased slightly to 394.398. The inclusion of $C_{DD\_65} \times C_{DD\_65}$ lag 7 ($\beta = -0.0002$, $p < 0.001$) (fourth model) improved the residual variance and AIC substantially to 0.662 and 378.828, respectively. The models estimated with climate variables were a better fit than the model without any climate variables. Linear regression with predictor variables entered as the independent variables resulted in an R value of 0.745 and an adjusted R^2 value of 0.548. Other climate variables were not significantly associated with the weekly *Ae. vexans* populations after adjustment for autocorrelation and seasonality.

Four models for *Cx. pipiens-restuans* are presented in Table 4, ranging from a model without any climate variables to a model including three climate variables (Fig. 4). The basic *Cx. pipiens-restuans* model without climate variables includes moving average ($\beta = 0.6507$, $p < 0.001$) and seasonal autoregressive ($\beta = -0.5597$, $p < 0.001$) process components. The best one-variable model included $C_{DD\_63} \times C_{DD\_63}$ at lag zero ($\beta = -0.001$, $p < 0.001$), and the model improved the residual variance from 0.407 to 0.340 (Table 6). The best two-variable model included both $C_{DD\_63} \times C_{DD\_63}$ at lag zero ($\beta = -0.001$, $p < 0.001$) and C_{DD_63} at lag eight ($\beta = 0.0067$, $p = 0.006$). The residual variance improved to 0.356. The best three-variable model included $C_{DD\_63} \times C_{DD\_63}$ at lag zero ($\beta = -0.001$, $p < 0.001$), CDD63 at lag eight ($\beta = 0.0069$, $p = 0.030$), and I_{Pcum} at lag zero ($\beta = 0.0124$, $p = 0.036$). The residual variance was 0.346. Linear regression of predictor vari-

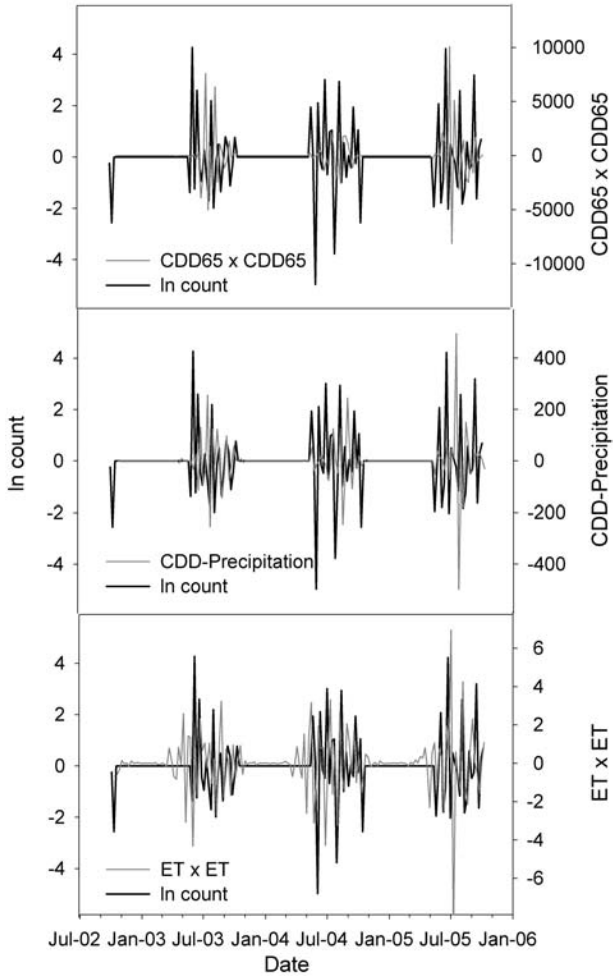

FIG. 1. Relationship between weekly *Aedes vexans* populations and significant climate variables. All series were prewhitened before analysis.

ables on the log-transformed count of *Cx. pipiens-restuans* resulted in an R-value of 0.420 and an adjusted R^2 value of 0.164.

Analysis of the autocorrelation function for residuals of all four *Ae. vexans* models and all four *Culex species* models showed that there were no significant spikes at important lags and there were no important lags where the Box-Ljung Q-statistic was significant. The most direct evidence of random residuals for a time series analysis is the absence of significant values of the Box-Ljung Q-statistic at lags of about one-quarter of the sample size (SPSS 2004). This analysis shows that the residuals in the models appear to fluctuate randomly around zero with no obvious trend in variation, and so all essential components of the model appear to be included.

The models that were developed with the data from 2001 through 2004 were validated with the 2005 mosquito season data by predicting the 2005 data and then comparing the prediction and its confidence intervals with the actual 2005 data. The prediction line captured the trend of the observed mosquito counts and passed through several of the observation points. All the actual data fall within the confidence intervals of the prediction (Figs. 5 and 6).

DISCUSSION

We developed multivariate SARIMA models for two vector mosquitoes of WNv using climate variables to improve the predictive ability of our forecasts. Meteorological variables

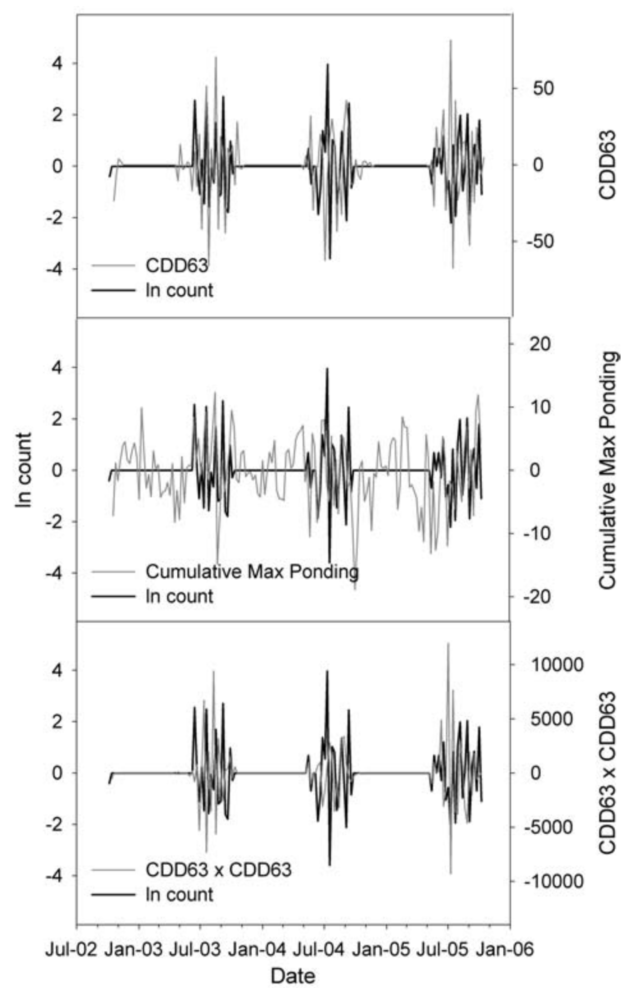

FIG. 2. Relationships between weekly *Culex pipiens-restuans* populations and significant climate variables. All series were prewhitened before analysis.

Table 3. Regression Coefficients from Multivariate SARIMA Models for *Aedes vexans*

	Model 0			Model 1			Model 2			Model 3		
	β	SE	p	β	SE	p	β	SE	p	β	SE	p
Autoregression 1	−0.4592	0.079	<0.001	−0.4023	0.080	<0.001	−0.4146	0.079	<0.001	−0.4461	0.079	<0.001
Autoregression 2	−0.2493	0.076	0.001	−0.2464	0.077	0.002	−0.2505	0.078	0.002	−0.1640	0.079	0.039
Seasonal autoregression	−0.4097	0.086	<0.001	−0.4304	0.087	<0.001	−0.3992	0.089	<0.001	−0.4402	0.084	<0.001
CDD-precipitation lag 2	–	–	–	−0.0032	0.001	0.002	−0.0030	0.001	0.003	−0.0033	0.001	0.001
ET × ET lag 5	–	–	–	–	–	–	0.1369	0.053	0.011	0.1399	0.050	0.006
CDD65 × CDD65 lag 7	–	–	–	–	–	–	–	–	–	−0.0002	0.000	

β, parameter estimate; SE, standard error of the parameter estimate; p, significance.

Table 4. Regression Coefficients from Multivariate SARIMA Models for *Culex pipiens-restuans*

	Model 0			Model 1			Model 2			Model 3		
	β	SE	p	β	SE	p	β	SE	p	β	SE	p
Moving average	0.6507	0.059	<0.001	0.8027	0.043	<0.001	0.7384	0.051	<0.001	0.7550	0.050	<0.001
Seasonal autoregression	−0.5597	0.071	<0.001	−0.6163	0.067	<0.001	−0.5910	0.070	<0.001	−0.6014	0.070	<0.001
CDD63 × CDD63 lag 0	–	–	–	−0.0001	0.000	<0.001	−0.0001	0.000	<0.001	−0.0001	0.000	<0.001
CDD63 lag 8	–	–	–	–	–	–	0.0067	0.003	0.037	0.0069	0.003	0.030
Cum max ponding lag 0	–	–	–	–	–	–	–	–	–	0.0124	0.006	0.036

β, parameter estimate; SE, standard error of the parameter estimate; p, significance.

significantly improved predictions of *Ae. vexans* abundance but contributed less substantially to predictions of *Cx. pipiens-restuans*. *Cx. pipiens-restuans* is an important vector that is likely involved in both early season enzootic transmission and late season epizootic amplification of WNv in North America, whereas *Ae. vexans* is a possible bridge vector of the virus to humans (Turell et al. 2000, Nasci et al. 2001, Andreadis et al. 2004, Turell et al. 2005). Although the effects of temperature on the rate of mosquito development are well understood in general, these effects have not been quantified for specific mosquito species in the field. Similarly, the requirement of water in the first three stages of mosquito development is a biological fact, but the direct effect of net precipitation on mosquito abundance has not been explored in temperate climates (Pratt and Moore 1993, DeGaetano 2005).

To the best of my knowledge this is a first attempt at developing a time series model of weekly mosquito abundance in a temperate climate setting since Hacker et al. (1973) analyzed three sets of mosquito data with the Box-Jenkins approach. The results of the current study suggest that climate factors may allow for better predictions of the time when mosquito vector populations will emerge, and when the respective population sizes will reach the level of a public health threat. However, the coefficients of the meteorological effects are difficult to interpret directly because of the logarithm and differencing transformations of vector abundance needed to ensure stationarity. The key determinants of *Ae. vexans* populations included two autoregressive process components, a seasonal autoregressive component, and the interactive CDD-precipitation variable at a lag of two weeks. The significance of $C_{DD\_65} \times P_{week\_4}$ as a predictor of *Ae. vexans* populations shows that the interaction between temperature and precipitation is an important index of vector mosquito abundance. Temperature and precipitation are both essential to the life cycle development of mosquito vectors, but they have rarely been combined as an index to enable the prediction of mosquito populations. Our simple index should be tested for importance in forecasting other mosquito vector populations in other temperate regions where temperature is a limiting factor for mosquito development. The other two independent variables that helped forecast *Ae. vexans* abundance were $E_T \times E_T$ at a lag of five weeks and $C_{DD\_65} \times C_{DD\_65}$ at a lag of seven weeks. Evapotranspiration is directly related to temperature and also reflects the amount of surface wetness in the environment. *Ae. vexans* is a floodwater mosquito that requires fresh water flooding for eggs to hatch (Pratt and Moore 1993). Other studies have found a significant correlation between a surface wetness index and *Ae. vexans* abundance (Shaman et al. 2002).

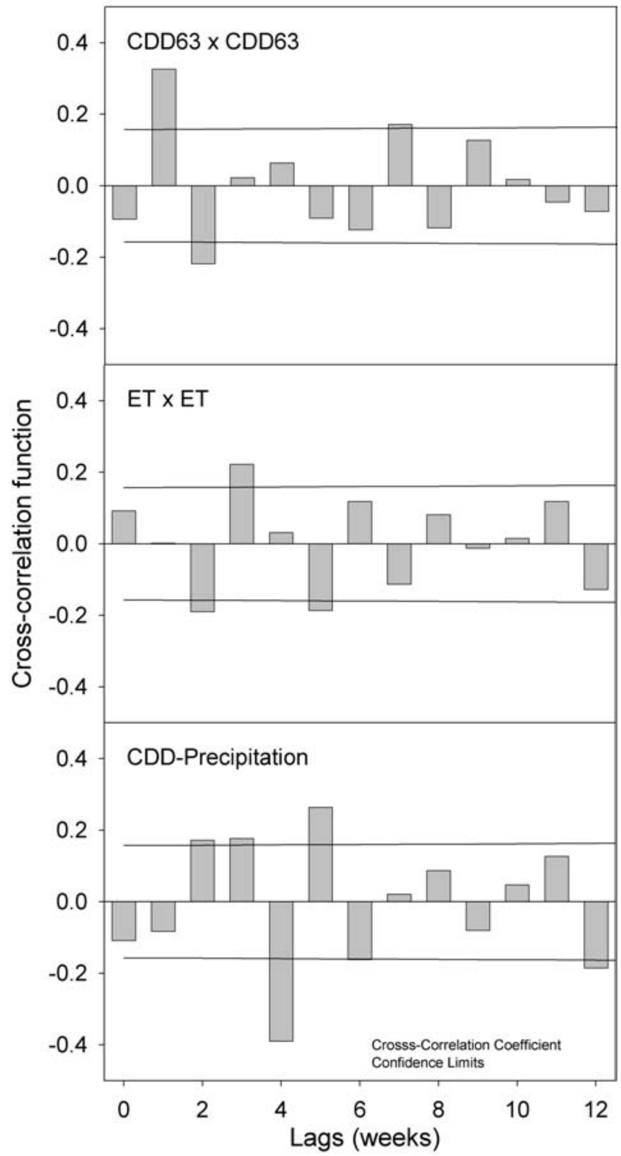

FIG. 3. Significant lags between *Aedes vexans* and climate variables from cross-correlation analysis.

The $C_{DD\_65} \times P_{week\_4}$ variable illustrates a similar relationship as the evapotranspiration variable, both including temperature and moisture to some degree. However, the important squared term of evapotranspiration illustrates that the relationship is nonlinear. The effect of evapotranspiration is a positive exponential but is likely to level out at an undetermined point where temperature and water are sufficient to maintain populations of *Ae. vexans*. The third significant predictor of *Ae. vexans* population abundance was also a squared term, $C_{DD\_65} \times C_{DD\_65}$ at a lag of seven weeks, indicating that the relationship between cooling degree days and abundance of *Ae. vexans* is nonlinear. This might be expected because mosquito populations need a threshold temperature for development. The seven week lag between C_{DD_65} and mosquitoes trapped is a good indication of the amount of time it takes for *Ae. vexans* populations to build up after the weather turns warm enough for their development in this temperate climate. The results of the linear regression analysis show that the climatological variables explain 55% of the variation in population abundance of *Ae. vexans* in Western New York. These variables may be used to assist in predicting the timing of mosquito emergence to improve control efforts of these vector species.

The model predicts emergence of *Ae. vexans* a little earlier in the season than the data suggest, but overall the autoregressive $(2,1,0)(1,1,0)_{52}$ model with climate variables does a good job of forecasting the abundance of this species in the validation period (Fig. 5). Three distinct peaks of *Ae. vexans* abundance are evident in the data and are modeled adequately (Andreadis et al. 2004). The model with three predictors of abundance was a better predictor of the late season low mosquito count than the model with no predictors. All independent variables included in the model are true predictors, as they were lagged from the mosquito abundance data.

The key determinants of *Cx. pipiens-restuans* included moving average and seasonal autoregression process components. These mosquitoes over-winter as adults that lay their eggs in the spring. The moving average component indicates that the process that created the time series is dependent upon recent deviations from the mean. This may be because of the numbers of mosquitoes that are able to survive the winter. The significant predictor variables of *Cx. pipiens-restuans* populations are $C_{DD\_63} \times C_{DD\_63}$ at a lag of zero weeks, C_{DD_63} at a lag of eight weeks, and I_{Pcum}, also at a lag of zero weeks. These results indicate that temperatures above the threshold of 63°F allow for the development of *Cx. pipiens-restuans*. Hacker also found a minimum threshold temperature was necessary before a peak in *Culex tarsalis* abundance would occur in Iowa (Hacker et al. 1973). The eight-week lag of C_{DD_63} may reflect the amount of time it takes for consistent warmth to establish in the temperate study area, where temperatures often fluctuate during the spring. Correlation of I_{Pcum} at lag zero with *Cx. pipiens-restuans* populations may indicate moist conditions favorable to mosquito activity. Linear regression analysis of *Cx. pipiens-restuans* populations with the significant predictor variables indicated that only 16% of the variation could be ascribed to the weather variables. However, the models for this species had an overall lower root mean square value, indicating that they do a good predictive job without the inclusion of the weather variables.

All four $(0,1,1)(1,1,0)_{52}$ models presented for *Cx. pipiens-restuans* forecast the abundance of this species very well (Fig. 6). These models

TABLE 5. *AEDES VEXANS* MULTIVARIATE SARIMA MODEL DIAGNOSTICS

	Variables added	*Residual variance*	*Akaike's information criterion*	*Schwarz's Bayesian criterion*
Model 0	No predictors	0.768	414.579	423.729
Model 1	CDD-precipitation lag 2	0.735	402.452	414.574
Model 2	ET × ET lag 5	0.726	394.398	409.485
Model 3	CDD65 × CDD65 lag 7	0.662	378.828	396.852

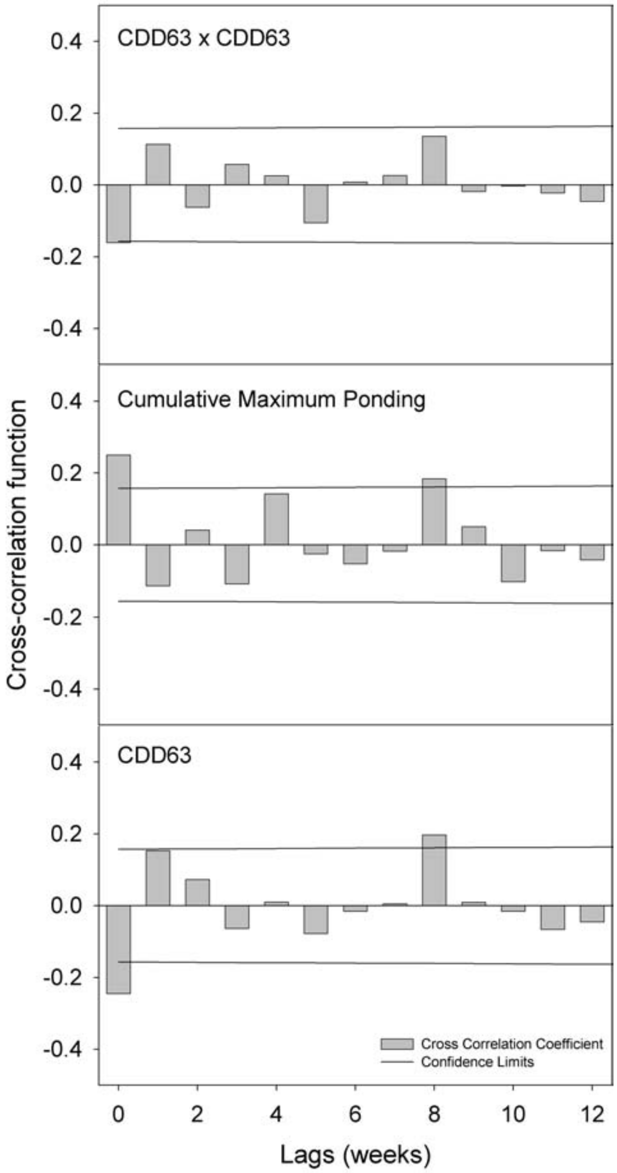

FIG. 4. Significant lags between *Culex pipiens-restuans* and climate variables from cross-correlation analysis.

also predict the timing of the emergence of this species, but the models have a harder time with the low count just after the initial peak during the validation period. Two of the independent variables included in these models, $C_{DD\_63} \times C_{DD\_63}$ and I_{Pcum}, are not true predictors in that they were significant during the same time period as the abundance data (lag 0). Meteorological data from previous time periods are true predictors of mosquito abundance, whereas those from the current time period demonstrate the influence of weather conditions on mosquito catch (DeGaetano 2005). This being the case, the only true predictor of *Cx. pipiens-restuans* population levels is C_{DD_63} at a lag of eight weeks (Williams 1961, Cross et al. 1988).

Given the variability of weather conditions and the relatively short time series included in this study, improvements of these forecasting models may be possible after more data on mosquito abundance is available. Long term datasets of mosquito abundance are relatively uncommon but are needed to improve the predictive capability of forecasts. The emergence of West Nile virus in the United States has motivated many state and local officials to begin monitoring populations of vector mosquitoes in all parts of the country, providing opportunities to quantify the relationships between weather factors and specific species abundances. Autocorrelation of mosquito population levels is an important factor to investigate in these forthcoming models. Box-Jenkins models are mathematical models that predict present values of a variable from its past values. They have been widely used in economics, but their use is becoming more common in other areas of research, including epidemiology and vector control efforts (Alberdi Odriozola et al. 1998, Hu et al. 2004, Naish et al. 2006). The ability to link these mathematical models to actual biological controls of vector abundance through meteorological factors should be explored further. Use of these models in forecasting disease incidence has been successful,

TABLE 6. *CULEX PIPIENS-RESTUANS* MULTIVARIATE SARIMA MODEL DIAGNOSTICS

	Variables added	*Residual variance*	*Akaike's information criterion*	*Schwarz's Bayesian criterion*
Model 0	No predictors	0.407	325.767	331.867
Model 1	CDD63 × CDD63 lag 0	0.340	305.080	314.229
Model 2	CDD63 lag 8	0.356	297.451	309.466
Model 3	Cum max ponding lag 0	0.346	294.962	309.982

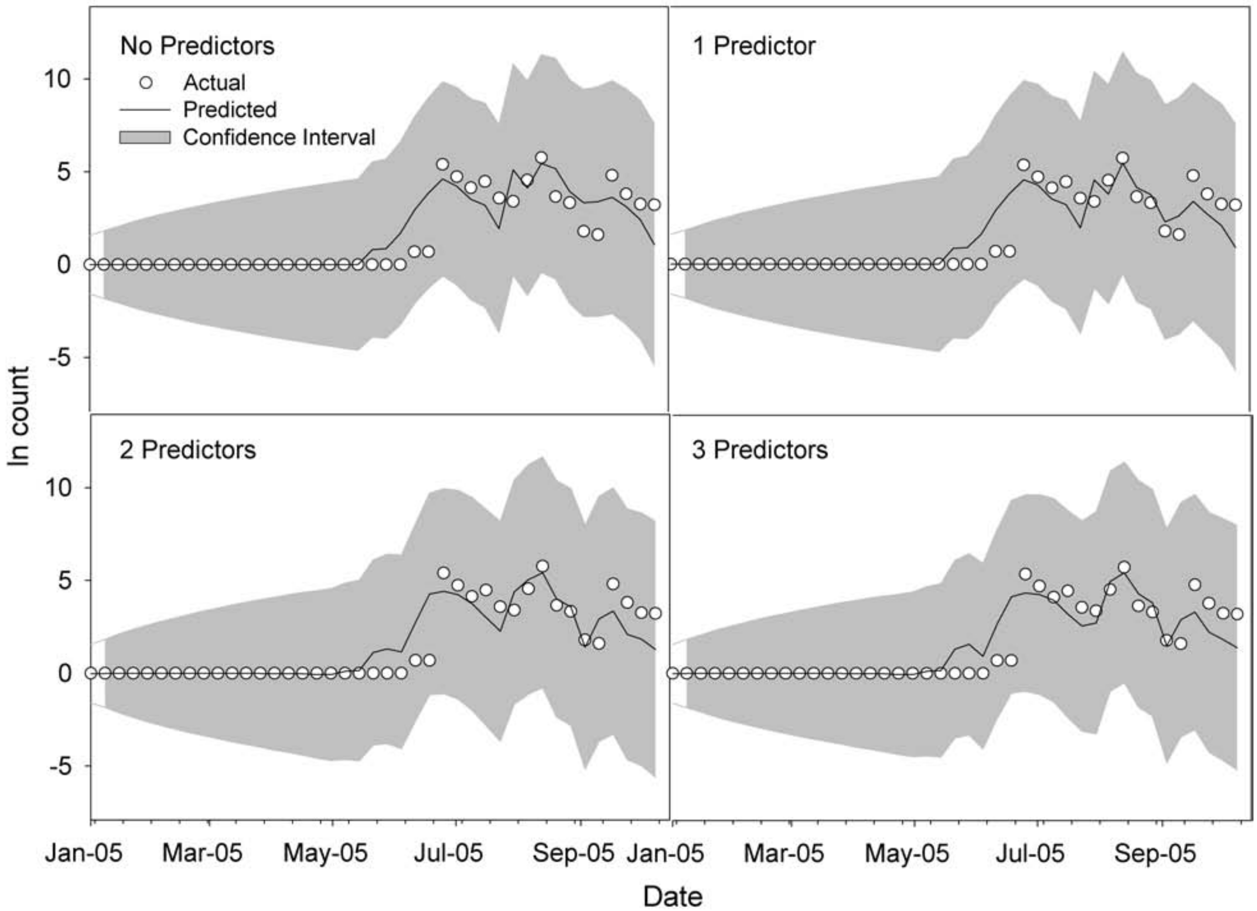

FIG. 5. *Aedes vexans* multivariate SARIMA model validations. One predictor model includes CDD-precipitation at lag two, two predictor model includes CDD-precipitation at lag two, and ET × ET at lag five, three predictor model includes CDD-precipitation at lag two, ET × ET at lag five, and CDD65 × CDD65 at a lag of seven.

but many disease incidence counts are too low to use this technique on a weekly basis (Hu et al. 2004). By performing the time series analysis on vector abundance instead of disease incidence, weekly predictions can be made, allowing for a significant improvement in the precision of forecasts.

A shortcoming of this study is the lack of data on micrometeorological conditions. Localized climate has a strong effect on the capture of mosquitoes in light traps. Wind speed and wind direction particularly affect migration of mosquitoes during peak activity hours. Future studies may address this shortcoming with the inclusion of wind speed, wind direction, and peak wind gusts in the cross-correlation analysis. Another possible shortcoming to this study is the grouping of *Cx. pipiens* and *Cx. restuans* abundance data. Although previous studies have also grouped these species together as a complex (DeGaetano 2005, Kilpatrick et al. 2005, White et al. 2006), other research has shown that *Cx. restuans* is the predominate species in the early summer, whereas *Cx. pipiens* is predominant in the late summer with a crossover occurring between late July and early September (Lampman et al. 1997, Andreadis et al. 2004, Kunkel et al. 2006, Lampman et al. 2006). The grouping of an early season mosquito with a late season mosquito may explain why meteorological factors were less important for predicting *Cx. pipiens-restuans* abundance.

Precipitation and temperature both control the emergence of mosquito populations in temperate climates, but these relationships have not generally been quantified. Mosquitoes have pupal and larval stages that require water. Dif-

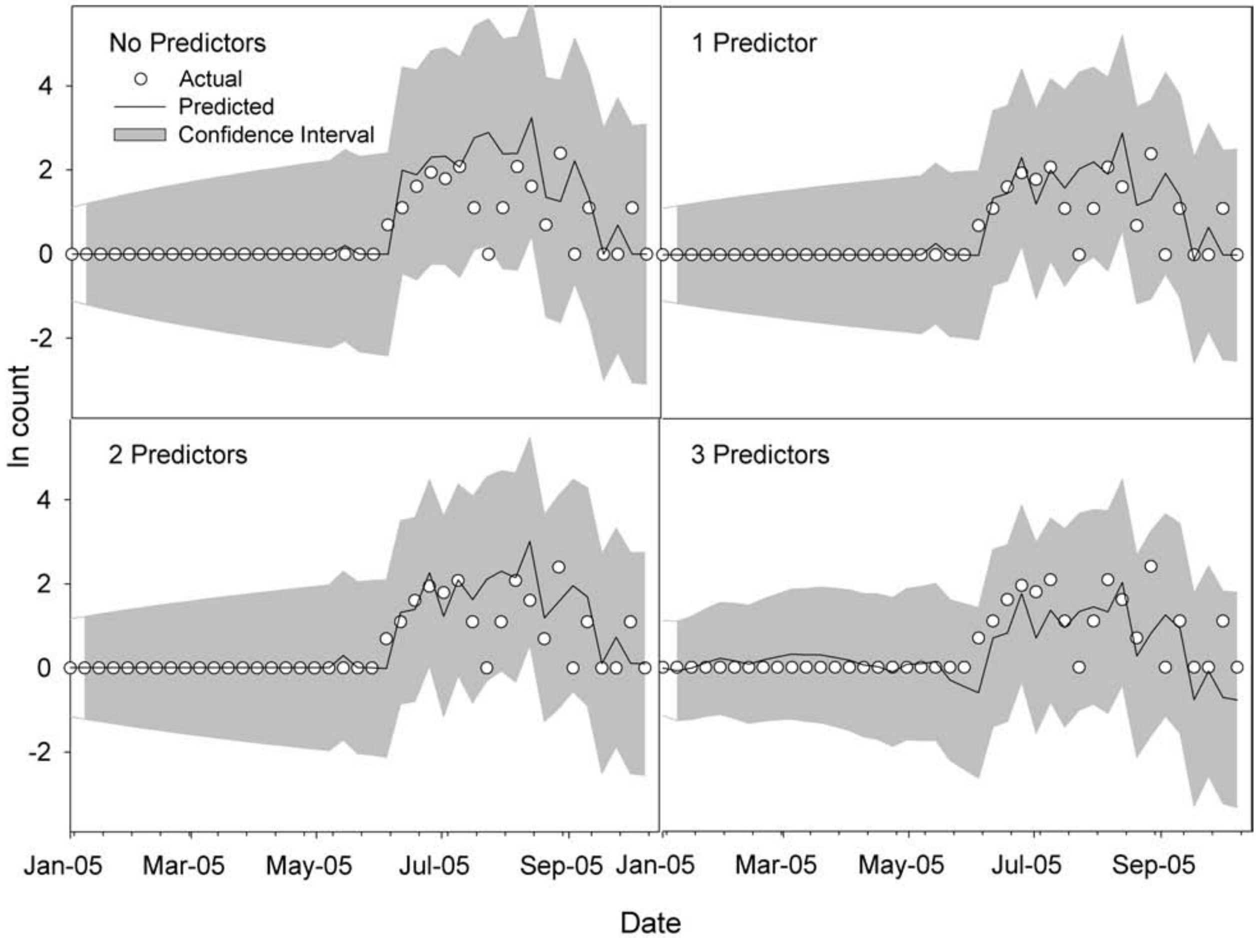

FIG. 6. *Culex pipiens-restuans* multivariate SARIMA model validations. One predictor model includes CDD63 × CDD63 at a lag of zero, two predictor model includes CDD63 × CDD63 at a lag of zero, and CDD63 at a lag of eight, three predictor model includes CDD63 × CDD63 at a lag of zero, CDD63 at a lag of eight, and cumulative maximum ponding at a lag of zero.

ferent species prefer different water habitats and may have different relationships with precipitation and temperature. Both *Cx. pipiens-restuans* and *Ae. vexans* mosquitoes produce several generations per year, but they differ in their method of surviving the winter. *Cx. pipiens-restuans* overwinter as mated adults that lay their eggs in the spring. *Ae. vexans* lay their eggs before the winter, but the eggs won't hatch until flooding occurs in the spring. These biological differences in species may explain the differences between simple autoregressive (p) and simple moving average (q) portions of the time series models, both needing the seasonal autoregressive process component to model adequately the time series of abundances (P). The length of the time series in the current study is relatively short, however, and the models may be improved as more data become available. This research is unique in its use of weekly climate and mosquito data. Previous studies have focused on monthly climate and mosquito or disease information (Hu et al. 2004), and these earlier studies have not had the regular weekly sampling schemes needed to develop an ARIMA model (Andreadis et al. 2004). The finer resolution of weekly data will enable a more accurate pinpointing of the precise time that mosquito control efforts need to be concentrated. Time series analyses of other species in temperate climates are needed to develop a baseline of mosquito populations before global climate change affects the abundance of mosquitoes.

ACKNOWLEDGMENTS

The authors would like to thank Peter Tripi, Glenn Robert, and John Eiss of the Erie County Health Department, Vector Control Program, for providing all the mosquito vector data.

REFERENCES

Abeku, TA, De Vlas, SJ, et al. Effects of meteorological factors on epidemic malaria in Ethiopia: a statistical modelling approach based on theoretical reasoning. Parasitology 2004; 128:585–593.

Alberdi Odriozola, JC, Díaz Jiménez, J, et al. Air pollution and mortality in Madrid, Spain: a time-series analysis. Int Arch Occ Env Hea 1998; 71:543–549.

Allard, R. Use of time-series analysis in infectious disease surveillance. B World Health Organ 1998; 76:327–333.

Andreadis, TG, Anderson, JF, et al. Epidemiology of West Nile virus in Connecticut: a five-year analysis of mosquito data 1999–2003. Vector-Borne Zoonot 2004; 4:360–378.

Box, GEP, Jenkins, G. *Time Series Analysis, Forecasting and Control*. San Francisco, Holden-Day, 1990.

Box, GEP, Jenkins, GM. *Time Series Analysis: Forecasting and Control*. San Francisco, HoldenDay, 1976.

Campbell, GL, Marfin, AA, et al. West Nile virus. Lancet Infect Dis 2002; 2:519–529.

Carpenter, SJ, LaCasse, WJ. *Mosquitoes of North America (North of Mexico)*. Berkeley, University of California, 1955.

CDC. *Epidemic/Epizootic West Nile Virus in the United States: Guidelines for Surveillance, Prevention, and Control*. Washington DC, Centers for Disease Control and Prevention U.S. Department of Health and Human Services, 2003.

Cross, ER, Bailey, RC, et al. A quantitative investigation of the seasonal occurrence of Culex tritaeniorhynchus in Okinawa. Environ Int 1988; 14:11–18.

DeGaetano, AT. Meteorological effects on adult mosquito (*Culex*) populations in metropolitan New Jersey. Int J Biometeorol 2005; 49:345–353.

Diuk-Wasser, MA, Brown, HE, et al. Modeling the spatial distribution of mosquito vectors for West Nile virus in connecticut, USA. Vector-Borne Zoonot 2006; 6:283–295.

ECDOH. West Nile Virus and Other Arbovirus Five Year Surveillance Report: 2000–2004. E. C. N. Y. Erie County Department of Health, 2005.

Hacker, CS, Scott, DW, et al. Time series analysis of mosquito population data. J Med Entomol 1973; 10:533–543.

Hayes, RO, Maxwell, EL, et al. Detection, identification, and classification of mosquito larval habitats using remote sensing scanners in earth-orbiting satellites. Bull World Health Organ 1985; 63:361–374.

Hu, W, Nicholls, N, et al. Development of a predictive model for Ross River Virus disease in Brisbane, Australia. Am J Trop Med Hyg 2004; 71:129–137.

Kilpatrick, AM, Kramer, LD, et al. West Nile virus risk assessment and the bridge vector paradigm. Emerg Infect Dis 2005; 11:425–429.

Kuhn, KG, Campbell-Lendrum, D, et al. *Using Climate to Predict Infectious Disease Outbreaks: A Review*. World Health Organization, 2004.

Kunkel, KE, Novak, RJ, et al. Modeling the impact of variable climatic factors on the crossover of *Culex restuans* and *Culex pipiens* (Diptera: Culicidae), vectors of West Nile virus in Illinois. Am J Trop Med Hyg 2006; 74:168–173.

Lampman, R, Hanson, S, et al. Seasonal abundance and distribution of mosquitoes at a rural waste tire site in Illinois. J Am Mosquito Contr 1997; 13:193–200.

Lampman, R, Slamecka, M, et al. *Culex* population dynamics and West Nile virus transmission in East-Central Illinois. J Am Mosquito Contr 2006; 22:390–400.

Leaf, A. Potential health effects of global climatic and environmental changes. New Engl J Med 1989; 321: 1577–1583.

Longstreth, J. Public health consequences of global climate change in the United States—some regions may suffer disproportionately. Environ Health Persp Suppl 1999; 107(S1):169–179.

McCleary, R, Hay, R. *Applied Time Series Analysis for the Social Sciences*. Beverly Hills: age Publications, 1980.

Means, R. *Mosquitoes of New York. Part II. Genera of Culicidae Other than Aedes Occurring in New York (Bulletin 430b)*. Albany: New York State Museum, 1987.

Means, RG. *Mosquitoes of New York. Part I. The Genus Aedes Meigen with Identification Keys to Genera of Culicidae (Bull. 430a)*. Albany: New York State Museum, 1979.

Naish, S, Hu, W, et al. Weather variability, tides and Barmah Forest Virus Disease in the Gladstone Region, Australia. Environ Health Persp 2006; 114:678–683.

Nasci, RS, White, DJ, et al. West Nile virus isolates from mosquitoes in New York and New Jersey, 1999. Emerg Infect Dis 2001; **7**:626–663.

Nash, D, Mostashari, F, et al. The outbreak of West Nile virus infection in the New York City area in 1999. New Engl J Med 2001; 344:1807–1814.

Pratt, HD, Moore, CG. *Mosquitoes of Public Health Importance and Their Control*. Atlanta: Centers for Disease Control and Prevention, United States Department of Health and Human Services, 1993.

Shaman, J, Stieglitz, M, et al. Using a dynamic hydrology model to predict mosquito abundances in flood and swamp water. Emerg Infect Dis 2002; 8:6–13.

SPSS, I. *SPSS Trends 13.0*. SPSS Inc., 2004.

Stojanovich, CJ. Illustrated key to common mosquitoes of northeastern North America. Atlanta: Cullom and Gherter, 1961.

Tong, S, Bi, P, et al. Climate variability and Ross River virus transmission, J Epidemiol Comm Health 2002; 56:617–621.

Tong, S, Hu, W, et al. Climate variability and Ross River virus transmission in Townsville Region, Australia, 1985–1996. Trop Med Int Health 2004; 9:298–304.

Turell, MJ, Dohm, DJ, et al. An update on the potential of North American mosquitoes (Diptera: Culicidae) to transmit West Nile virus. J Med Entomol 2005; 42:57–62.

Turell, MJ, O'Guinn, M, et al. Potential for New York mosquitoes to transmit West Nile virus. Am J Trop Med Hyg 2000; 62:413–414.

White, BJ, Andrew, DR, et al. West Nile virus in mosquitoes of northern Ohio, 2003. Am J Trop Med Hyg 2006; 75:346–349.

Williams, CB. Studies in the effect of weather conditions on the activity and abundance of insect populations. Philos T Roy Soc B 1961; 244:331–378.

Address reprint requests to:
P. R. Trawinski
Department of Geography
State University of New York at Buffalo
Wilkeson Quad
Buffalo, New York 14261

E-mail: prt@buffalo.edu